On the use of model order for detecting potential target locations in SAR images

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ABSTRACT

The Region of Interest (ROI) detection stage of an Automatic Target Recognition (ATR) System serves the crucial role of identifying candidate regions which may have potential targets. The large variability in clutter (noise or countermeasures which provide target like characteristics) complicate the task of developing accurate ROI determination algorithms.

Presented in this paper is a new paradigm for ROI determination based on the premise that disjoint local approximation of the regions of a SAR image can provide discriminatory information for clutter identification. Specifically, regions containing targets are more likely to require complex approximators (i.e. ones with more free parameters or a higher model order).

We show preliminary simulations results with two different approximators (sigmoidal multi-layered neural networks with lateral connections, and radial basis function neural networks with a model selection criterion), both of which attempt to produce a smooth approximation of disjoint local patches of the SAR image with as few parameters as possible. Those patches of the image which require a higher model order are then labeled as ROIs. Our preliminary results show that sigmoidal networks provide a more consistent estimate of the model order than their radial basis function counterparts.

Keywords: Synthetic Aperture Radar, Automatic Target Recognition, Detection, Clutter, Neural Networks, Region of Interest

1. INTRODUCTION

Automatic Target Recognition (ATR) in its simple form consists of the three steps shown below:

1. Region of Interest (ROI) or focus of attention determination.
2. Extraction of features from the regions identified in Step 1 above.
3. Classification of the object (if any) in the ROI based on the features extracted in Step 2 above.

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When information from multiple sensors is available, one can form a single data stream on which the above three steps can be applied. This could be termed as data level fusion. Alternatively, each of the three steps may be independently applied to each data stream followed by a categorization which is negotiated between the categorization obtained from each data stream (decision level fusion). Time varying information (motion provides a clue as to the functionality of the observed) can also provide discriminatory information.

Irrespective of the suite of sensors used, ROI determination is an important step in any ATR system. When the ROI determination stage produces a high rate of false alarms (ROIs which are discovered by later recognition stage algorithms to contain only clutter) a significant amount of time is wasted. The ROI determination stage thus has to reduce the false alarm rate while ensuring that regions with targets in them are not missed.

Within the context of Synthetic Aperture Radar (SAR) images, there have been a number of approaches proposed for ROI determination. When the clutter characteristics are stationary and Gaussian, the so called Constant False Alarm Rate (CFAR) filter, which uses the pixel intensity relative to the local mean can be used (see[1] for modifications in the non-Gaussian case). Various filters (such as the whitening filter,[2] or BCS/FCS[3]) can be used to enhance the contrast prior to CFAR application. Multi-parameter CFAR may also be used.[4] A macro Gabor filter composed of a set of real Gabor functions has also been proposed.[5]

The region of interest selection can itself utilize Steps 2 and 3 outlined above. Thus features may be extracted (say from disjoint squares) and a classifier constructed to label a square as 'interesting' or otherwise. For example,[6] a feed-forward neural network trained using back-propagation[7] is used to obtain ROIs. Inputs to this network are derived from Gabor filters. A similar approach reported uses radial basis function neural networks operating on the wavelet decomposition of an image to obtain regions of interest.[8]

A disadvantage of any supervised ROI determination scheme is that its performance is directly influenced by the amount and quality of data that was used in training it. Due to the large variability of clutter characteristics it may be very difficult to arrive at a training data set which captures this variability. Consequently, adaptive clutter characterization approaches have also been proposed. These approaches assume that there will always be a large amount of clutter available in a SAR image and hence adaptive characterization is possible. For example, a Gibbs distribution model can be constructed towards approximating the joint pdf of pixels.[9] Such a pdf can be used in Bayesian inference to ascertain if an image region is consistent with the pdf or deviates from it. In related approaches, clutter is characterized based on statistical pattern recognition techniques.[10]

Other approaches include unsupervised methods based on vector quantization (with the number of clusters decided *a priori*) to obtain regions of interest.[8] Due to the difficulty in *a priori* deciding the number of clusters, the authors also report results using a topology representing network proposed by.[11]

This paper provides a novel approach to isolating regions of interest in SAR images. Our approach is based on function approximation, and unlike previous approaches, *does not* require the presence of a *good* training data set. Specifically, we obtain the lowest order model that can approximate the return in disjoint squares of a SAR image. Those disjoint squares that require a higher model order approximator (i.e. one with more free parameters) are then labeled as regions of interest. Towards obtaining the lowest model order approximation of disjoint squares in a SAR image, we use two different approximators. The first of these is a sigmoidal multi-layered feed-forward neural network with selected lateral connections amongst the hidden layer neurons.[12–14] The second of these is a radial basis function

Figure 1. Lateral connections in a feed-forward architecture. Inputs and hidden layer neurons are fully connected as are hidden layer and output layer neurons. Neuron j in the hidden layer also receives the net input of neuron $(j-1)$ in the hidden layer through a lateral connection

The adjustment of the weights are done to minimize the sum of squared error between the output y_i^μ and the desired output ζ_i^μ, i.e. $J = \sum_{\mu=1}^{p} J^\mu$, where:

$$J^\mu = \frac{1}{2}\sum_{i=1}^{o}(\zeta_i^\mu - y_i^\mu)^2 \tag{2}$$

To obtain the learning algorithm, we use gradient descent to minimize J^μ. For the hidden to the output layer weights, we obtain:

$$\Delta W_{ij}^\mu = -\eta\frac{\partial J^\mu}{\partial W_{ij}} = (\zeta_i^\mu - y_i^\mu)f'(s_i^\mu)z_j^\mu = \eta\delta_i^\mu z_j^\mu \tag{3}$$

where, $\delta_i^\mu = (\zeta_i^\mu - y_i^\mu)f'(s_i^\mu)$, and η is a constant (forward learning rate).

The weight update equations for the lateral weights are:

$$\Delta q_{j,j-1}^\mu = -\eta_q\frac{\partial J^\mu}{\partial q_{j,j-1}} = \eta_q\left[\underline{\delta}_j^\mu + \left(\sum_{\beta=j+1}^{m}\underline{\delta}_\beta^\mu\prod_{\alpha=j+1}^{\beta}q_{\alpha,\alpha-1}\right)\right]h_{j-1}^\mu \tag{4}$$

where, $\underline{\delta}_j^\mu = \left(\sum_{i=1}^{o}\delta_i^\mu W_{ij}f'(h_j^\mu)\right)$, and η_q is a constant (lateral learning rate). The update equations for the input to the hidden layer weights are similar to the above:

$$\Delta w_{jk}^\mu = -\eta\frac{\partial J^\mu}{\partial w_{jk}} = \eta\left[\underline{\delta}_j^\mu + \left(\sum_{\beta=j+1}^{m}\underline{\delta}_\beta^\mu\prod_{\alpha=j+1}^{\beta}q_{\alpha,\alpha-1}\right)\right]\xi_k^\mu \tag{5}$$

Further details on these weight update equations are available in.[12]

It has been proved[13,14] that if the forward weights are initialized to be equal, and the lateral weights are initialized to be equal, then update of the weights using equations (3)—(5) leads at convergence to the following: hidden neurons 1 through t differentiate, neurons t through T behave identically, and neurons T through m differentiate ($t < T < m$). Consequently, the model order at convergence is reflected by $(t + m - T)$.

2.2. RADIAL BASIS FUNCTION NETWORK

Radial basis function networks[15,16] are architecturally similar in topology to the standard feed-forward neural networks, i.e. they consist of an input layer which has n inputs, a hidden layer of m neurons with Gaussian (or multi-quadric) basis functions, and a layer of output neurons. In what follows, we use the notation that was introduced in the previous sub-section. The output of the network is then,

$$y_i^\mu = \sum_{j=1}^{m} W_{ij}z_j^\mu \tag{6}$$

where, z_j^μ is the output of the j^{th} basis function which assuming is Gaussian can be written as,

$$z_j^\mu = exp\left(-\frac{\|\xi^\mu - w_j\|^2}{\sigma_j^2}\right) \tag{7}$$

where w_j is the center of the Gaussian and σ_j reflects the spread of the Gaussian.

Once again, we can define a sum of squared error as in equation (2) and resort to gradient descent to minimize the sum of squared errors. To avoid gradient descent, one can fix the centers and the spreads of the Gaussians resulting in a linearly parameterized network for which the output-hidden weights can be found using the Moore-Penrose inverse. For example, if $\mathbf{Y}_{p\mathrm{x}o}$ denotes all the desired outputs, and $\mathbf{H}_{p\mathrm{x}m}$ denotes the response of the basis functions, then the output-hidden weights $\mathbf{W}_{m\mathrm{x}o}$ can be obtained with,

$$\mathbf{W} = (\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{Y} \tag{8}$$

Rather than *a-priori* specifying the number m of basis functions to use, one can incrementally add the basis functions relying on a model selection criterion (such as generalized cross-validation (GCV) or the Bayesian Information Criterion (BIC)) to provide the stopping condition. In this paper, we stop the addition of basis function at the point that BIC stops decreasing. The number of basis functions used are then indicative of the model order that we seek.

3. SIMULATION RESULTS

We present preliminary simulations here based on an image in the MSTAR (PUBLIC) CLUTTER CD-ROM.[18] The clutter CD-ROMs contain ground clutter imagery collected in the X-band at 1-foot resolution in stripmap mode at 15-degree depression angles. Since these images are very large (approximately 1784x1476), for this simulation, we isolated a 256x256 block starting from the top left corner of the image identified as HB06172 on the CD-ROM. The raw clutter image is shown in Figure 2, and the model order as determined by the two methods is shown in Figure 3. For the multi-layered sigmoidal feed-forward neural network we used, 2 inputs (x and y coordinates), 15 sigmoidal hidden neurons (and hence 14 lateral weights), and 1 sigmoidal output (magnitude of the return at (x, y)). The forward weights were initialized to 0.1, and the lateral weights were initialized to 0.01. The forward learning rate (η) w as 0.3, and the lateral learning rate (η_q) was 0.1. For the radial basis function network case, we also used 2 inputs (x and y coordinates) and 1 output neuron (magnitude of the return at (x, y)). The addition of neurons was stopped at the minima of BIC. From the results it may be seen that the sigmoidal network provide a more consistent estimate of the model order than does the radial basis function network. We suspect that this is primarily due to the local nature of radial basis function networks. Further, the low model order (targets typically give us a model order of 10 or higher) as obtained by the sigmoidal network indicates the lack of a target in the image which is consistent with the fact that this image is a ground clutter image.

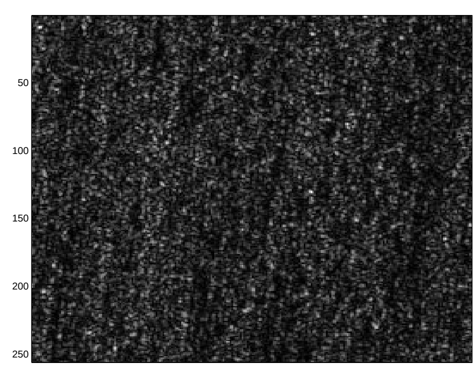

Figure 2. SAR clutter image

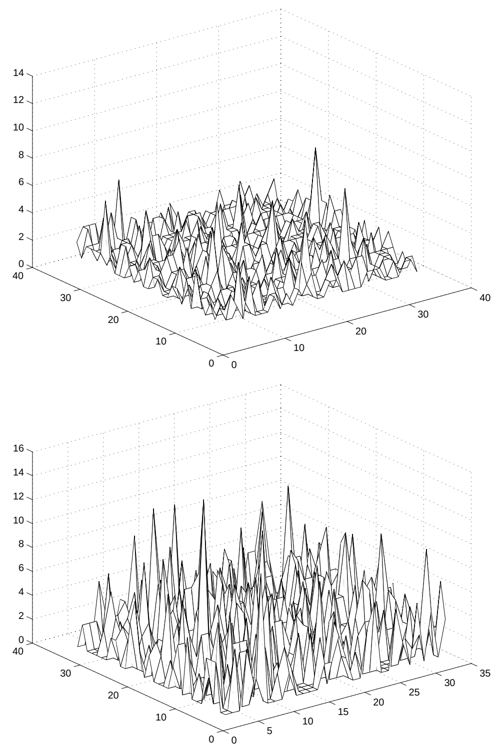

Figure 3. Model order for 8x8 blocks as determined by multi-layered sigmoidal feed-forward neural networks with lateral connections (top), and radial basis function network that optimize a model selection criterion (bottom)

4. CONCLUSIONS

In this paper we showed that the use of the model order of an approximator can serve as a valuable discriminatory tool in ROI determination. In particular, the sigmoidal multi-layered feed-forward neural networks seem to provide a consistent estimate of the model order. Though accurate, such determination the model order for each disjoint square is a time consuming process. In our future work, we seek to combine the speed of CFAR based approaches by evaluating CFAR labeled ROIs with the sigmoidal model order based approach proposed herein, when the underlying data distribution disagrees with that assumed in the CFAR model. This we anticipate will provide fast ROI determination without sacrificing the accuracy that the model order based approach seems to provide.

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